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DESIGN AND DEVELOPMENT OF AN AUTOMATED TOOL FOR JOB SHOP SCHEDULING USING PSO AND CPSO

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ABSTRACT

Scheduling of manufacturing systems refers to the determination of the sequence in which jobs are to be processed over the production stages, followed by the determination of the start time and finish time of processing jobs. This paper explores job shop scheduling to reduce makespan through Particle Swarm Optimization (PSO) and Chaotic Particle Swarm Optimization (CPSO) approaches. A Graphical User Interface (GUI) is designed to automate the steps involved in optimization of scheduling. The GUI provides the user flexibility in handling different machine systems and seamlessly integrates with decision making process. The results of the two optimization approaches are compared and Gantt chart of the schedule plotted.

KEYWORDS: Automated Tool, (PSO), Chaotic Particle Swarm Optimization (CPSO), GUI Provides

INTRODUCTION

Scheduling has been a subject of a significant amount of literature in the operations research field since the early 1950s [1] [2].The main objective of scheduling is an efficient allocation of shared resources over time to competing activities. Emphasis has been on investigating machine scheduling problems where jobs represent activities and machines represent resources. The problem is not only NP -hard, but also has a well-earned reputation of being one of the most computationally difficult combinatorial optimization problems considered to date. This intractability is one of the reasons why the problem has been so widely studied. The problem was initially tackled by "exact methods" such as the branch and bound method (BAB), which is based on the exhaustive enumeration of a restricted region of solutions containing exact optimal solutions. Exact methods are theoretically important and have been successfully applied to benchmark problems, but sometimes they are quite time consuming even for moderate-scale problems. With a rapid progress in computer technology, it has become even more important to find practically acceptable solutions by "approximation methods" especially for large-scale problems within a limited amount of time [2]. Stochastic local search methods are such approximation methods for combinatorial optimization. They provide robust approaches to obtain high quality solutions to problems of realistic sizes in reasonable amount of time. Some of stochastic local search methods are proposed in analogies with the processes in nature, such as statistical physics and biological evolution, and others are proposed in the artificial intelligence contexts. They often work as an iterative master process that guides and modifies the operations of subordinate heuristics; thus they are also called metaheuristics.

Metaheuristics have been applied to wide variety of combinatorial optimization problems with great success. Particle swarm optimization was developed by Kennedy and Eberhart (1995) as a stochastic optimization algorithm based

on social simulation models. The algorithm employs a population of search points that moves stochastically in the search space. Concurrently, the best position ever attained by each individual, also called its experience, is retained in memory. This experience is then communicated to a part or to the whole population, biasing its movement towards the most promising regions detected so far. The communication scheme is determined by a fixed or adaptive social network that plays a crucial role as to the convergence properties of the algorithm [3]. The PSO algorithm searches for the best solution over the complex space through co-operation and competition. First of all, the PSO algorithm creates the initial particle swarm, namely, it initializes a swarm of particle randomly in the available solution space, making each particle an available solution of the optimization problem. Furthermore, the target function determines the fitness value through the target function. Each particle will move in the space of the solution, with its direction and distance determined by speed. The general particle will move following the best current particle, obtaining the best solution by searching generation by generation [4][5]. In each generation, the particle will trace two limited values, one of which is the best solution, *pbest*, which is found so far by the particle itself. The other is the best solution, *gbest*, which has been found so far by general group swarm[6].

JSP MATHEMATICAL MODEL

Scheduling is the allocation of shared resources over time to competing activities. The *n*m* job shop scheduling problem, designated by the symbols $n/m/G/C_{max}$ can be described by a set of *n* jobs $\{j_i\}_{1<j<n}$ which is to be processed on *m* machines $\{m_r\}_{1<r<m}$. Job shop scheduling problem shall meet the following constrained conditions:

- Each machine can only process one working procedure of certain work piece in a period of time.
- Each working procedure will not be interrupted by other working procedures during the processing.
- Each work piece shall experience the processing on m machines, and during the processing, new work piece shall not be added, and the processing cannot be terminated.

The objective of optimizing the problem is to find a schedule that minimizes *Cmax*. .The objective function is defined as

$$c_{jr} = min\ (c_{max})$$

$\{Cjr\}1\leq j\leq n;1\leq r\leq m$ *is* the schedule of completion times for each operation that satisfies above constraints.*Cmax* is the time required to complete all the jobs is called the makespan, where

$Cmax = \max 1\leq j\leq n;1\leq r\leq mcjr.$

The processing of job *Jj* on machine *Mr* is called the *operation Ojr*. Operation *Ojr* requires the exclusive use of *Mr* for an uninterrupted duration *pjr*, its processing time; the preemption is not allowed. The starting time and the completion time of an operation *Ojr* is denoted as *s jr* and *cjr* respectively. The predefined technological sequence of each job can be given collectively as a matrix $\{T jk\}$ in which $T jk = r$ corresponds to the *k*-th operation *Ojr* of job *Ji* on machine *Mr*.

PSO AND CPSO

Particle swarm optimization (PSO) is a swarm intelligence algorithm that was put forward through the study on the bird swarm's flying behaviors. Similar to other optimization algorithm ideology, one particle denotes one bird in PSO,

and each particle is assigned an initial location and speed. During the particle swarm flying process, flying speed and orientation will be constantly adjusted, so as to find the optimal solution[8]. In PSO algorithm, particle constantly updates its speed and location according to *best P* and *best g* . When one particle finds one optimal local solution, other particles will be attracted by the optimal solution to gather around the solution rapidly. That will lead to premature convergence and local optimization, which will accordingly influence PSO's search performance[9][10]. Each particle updates its position based upon its own best position, global best position among particles and its previous velocity vector according to the following equations:

$$v_i^{k+1} = w \times v_i^k + c_1 \times r_1 \times (p_{best_i} - x_i^k) + c_2 \times r_2 \times (g_{best} - x_i^k) \quad (1)$$

$$x_i^{k+1} = x_i^k + \chi \times v_i^{k+1} \quad (2)$$

Where,

v_i^{k+1} : The velocity of i^{th} particle at $(k+1)^{th}$ iteration

w : Inertia weight of the particle

v_i^k : The velocity of i^{th} particle at k^{th} iteration

c_1, c_2 : Positive constants having values between [0, 2.5]

r_1, r_2 : Randomly generated numbers between [0, 1]

p_{best_i} :The best position of the i^{th} particle obtained based upon its own experience

g_{best} : Global best position of the particle in the population

x_i^{k+1}: The position of i^{th} particle at $(k+1)^{th}$ iteration

x_i^k : The position of i^{th} particle at k^{th} iteration

χ : Constriction factor. It may help insure convergence.

Suitable selection of inertia weight w provides good balance between global and local explorations.

$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter$ Where, $w_{\max}$ is the value of inertia weight at the beginning of iterations, $w_{\min}$ is the value of inertia weight at the end of iterations, $iter$ is the current iteration number and $iter_{\max}$ is the maximum number of iterations.

Chaotic is a nonlinear system that is similar to the "Random" and has complex behaviors. Since Chaotic is sensitive to the initial value, it can easily jump out of the local minimum. Also, its search speed is very fast. The basic ideology for CPSO algorithm is: In each iterative process, exert chaotic perturbation on *best g* , and take it as particle updating position, so as to prevent particle positions from converging, otherwise it will search locally around the global optimal solution. A detailed block diagram of the proposed work is given in the figure below.

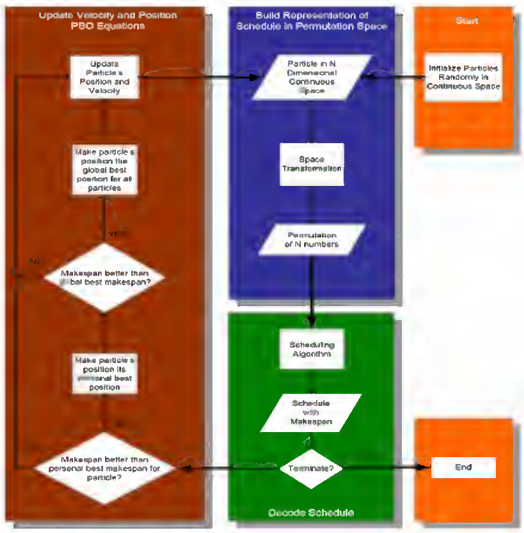

Figure 1: Block Diagram of the Proposed CPSO Method

BENCH MARK PROBLEMS

The three well-known benchmark problems with sizes of 6 _ 6, 10 _ 10 and 20 _ 5 (known as mt06, mt10 and mt20) formulated by Muth and Thompson [7] are commonly used as test beds to measure the effectiveness of a certain method. The mt10 and mt20 problems are almost similar. They are processing the same set of operations and technological sequences are similar, but in the mt20 problem, the number of machines available is reduced to half of that of the mt10 problem. For example, the first operation of each job in mt10 is exactly same as the first operation of each of the first 10 jobs in mt20 and the second operation of each job in mt10 is exactly same as the first operation of each of the second 10 jobs in mt20. Taillard proposed a set of 80 JSP and 120 FSP benchmark problems. They cover various ranges of sizes and difficulties. They are randomly generated by a simple algorithm. In this work 5 benchmark problems are considered namely mt06, mt10 and mt20 formulated by Moth and Thompson and Taillard's 15 jobs * 15 Machines and 30 jobs * 15 Machines problems.

MATLAB GRAPHICAL USER INTERFACE (GUI)

MATLAB is widely used in all areas of applied mathematics, in education and research at universities, and in the industry. MATLAB stands for MATrix LABoratory and the software is built up around vectors and matrices. This makes the software particularly useful for linear algebra but MATLAB is also a great tool for solving algebraic and differential equations and for numerical integration. MATLAB has powerful graphic tools and can produce nice pictures in both 2D and 3D. It is also a programming language, and is one of the easiest programming languages for writing mathematical programs. MATLAB also has some tool boxes useful for signal processing, image processing, optimization, etc.MATLAB has many advantages compared to conventional computer languages for solving technical problems. MATLAB is an

interactive system whose basic data element is an *array* that does not require dimensioning. The software package has been commercially available since 1984 and is now considered as a standard tool at most universities and industries worldwide

In this work MATLAB is used to code the proposed CPSO algorithm for having an effective job shop scheduling. Matlab is also used for designing the automated tool through a Graphical User Interface (GUI and scheduling as such is a very complex interconnected process where in different inputs in the form of machine type, machining sequence, machining time, may be needed in order to enforce a proper scheduling.

The GUI is coded using MATLAB Version 7.1 and is designed to enable the user to have seamless analysis of the data using different optimization methods. The data required for analysis is fed through an Excel sheet in predefined format. This helps in standardizing the input methods and helps in avoiding user induced errors.

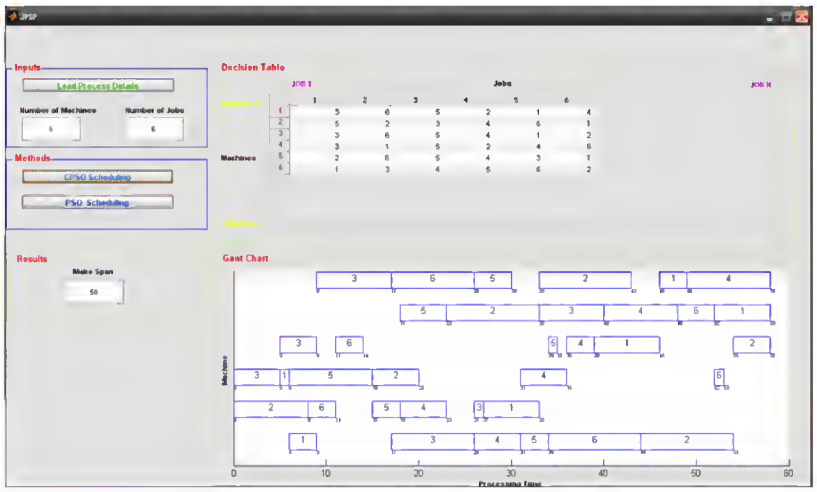

Figure 2: Screen Shot of the GUI Designed

From the GUI it can be observed that Input to the system can be given by pressing the Load Process Details switch. Once the data is loaded the number of machines and the number of jobs involved in the scheduling are displayed below. The user can then choose the required method for scheduling. The scheduling results are displayed in terms of make span of each proposed schedule, a decision table which tabulates the job sequence and a Gantt chart.

RESULTS AND CONCLUSIONS

The iteration settings for PSO include 100 maximum numbers of iterations, with acceleration constant of 2 and 2.5 and maximum and minimum inertia weights at 1 and 0.2 respectively. The maximum and minimum velocity of particles is fixed at 0.003 and -0.003 respectively. The simulations are carried out in a system having Core 2 Duo processor cloaking a speed of 2 GHz with a RAM of 2GB

Table 1: Make Span as Achieved by the Two Optimization Methods

Problem Size	Make Span Using PSO	Make Span Using CPSO
Mt06- 6 jobs * 6 Machines	61	58
Mt10- 10 jobs * 10 Machines	1039	970
Mt20- 20 jobs * 5 Machines	1312	1232
Tail lards 15 jobs * 15 Machines	1466	1345
Tail lards 30 jobs * 15 Machines	2975	2765

The Results of make span achieved by different optimization methods of PSO and CPSO are given in the Table 1. The results are best results achieved when each optimization method is run for 50 times. In the case of the mt06 problem there is 5 % reduction in make span in the case of CPSO method as compare to PSO. Similarly in the case of mt10 problem there is 6.6 % decrease in make span for the scheduled proposed using CPSO in comparison to that of the schedule proposed using PSO. In this case of Mt20 there is a 6 % reduction in make span . In this case of Tailard 15 jobs problem and 30 jobs problem there is 8.25% and 7.05% reductions respectively.

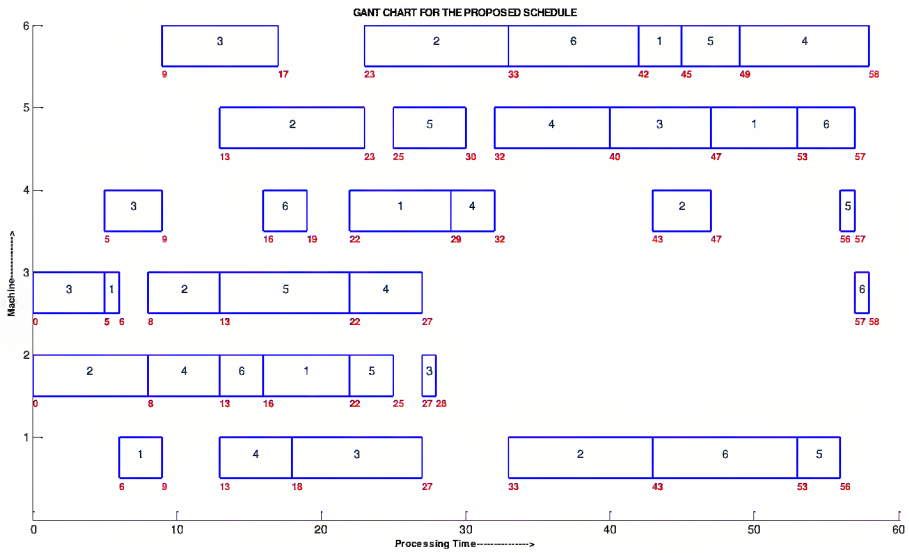

Figure 3: Gantt Chart as Plotted by the GUI for Mt06 Problem

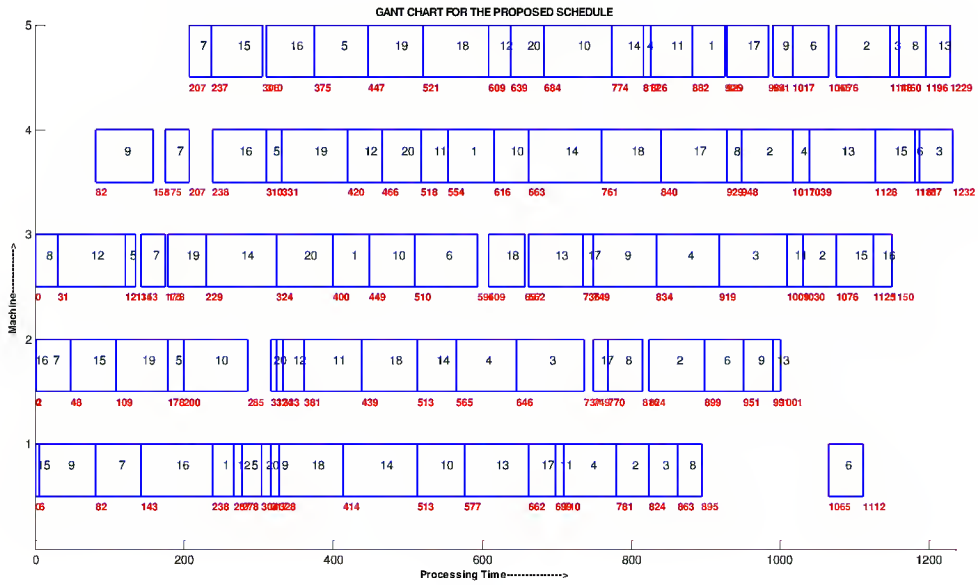

Figure 4: Gantt Chart as Plotted by the GUI for Mt20 Problem

The Gantt chart as plotted using the GUI is given for illustration. Figure 3 illustrates the Gantt chart of mt06 problem comprising 6 jobs and 6 machines and Figure 4 illustrates the Gantt chart of mt20 problem comprising 20 jobs and 5 machines

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